Diagnosis of Helicopter Gearboxes Using Structure-Based Networks

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DIAGNOSIS OF HELICOPTER GEARBOXES USING STRUCTURE-BASED NETWORKS

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Abstract

A connectionist network is introduced for fault diagnosis of helicopter gearboxes that incorporates knowledge of the gearbox structure and characteristics of the vibration features as its fuzzy weights. Diagnosis is performed by propagating the abnormal features of vibration measurements through this *Structure-Based Connectionist Network* (SBCN), the outputs of which represent the fault possibility values for individual components of the gearbox. The performance of this network is evaluated by applying it to experimental vibration data from an OH-58A helicopter gearbox. The diagnostic results indicate that the network performance is comparable to those obtained from supervised pattern classification.

1. INTRODUCTION

Present helicopter power trains are significant contributors to both flight safety incidents and maintenance costs. Power trains comprise almost 30% of maintenance costs and 22% of mechanically related malfunctions that often result in loss of life and the aircraft [1]. Future helicopters such as the LH and fixed wing aircraft like the ATF require increased levels of mission capability which cannot be met without advancing the state of the art in fault diagnosis. Fault diagnostic systems are necessary to detect failures in the power train reliably and rapidly, so as to allow scheduling of maintenance before a catastrophic failure occurs.

Fault diagnosis of helicopter gearboxes (like most rotating machinery) is based upon the detection of abnormalities in features of vibration such as the Root Mean Square (RMS), Kurtosis, Skewness, etc. A considerable effort has been directed towards identification of individual features that would be affected by specific faults in the gearbox [9]. The traditional approach to diagnosis has relied on human expertise to identify the abnormal features and to relate them to component faults. In this approach, a diagnostician would relate the abnormal features to component faults based on the component's proximity to the sensor producing the feature. Using the proximity information, along with the information about the specific fault that the abnormal feature represents, the diagnostician would hypothesize faults in various components. The hypothesis is then verified or discarded by examining the features from other sensors in the proximity of the suspect component. The advantage of the traditional approach is that it utilizes the structure of the gearbox to isolate faults. Its disadvantages stem from the difficulty associated with identifying abnormality in features that are contaminated with noise, in addition to processing the overwhelming number of features that are obtained from the sensors. Due to the large number of features and sensors associated with a gearbox, the diagnostician cannot pay equal attention to all the features and is likely to ignore information that contradicts the hypothesis.

In order to cope with noise as well as the multiplicity of information in the features, pattern classification through connectionist networks has been proposed as a means to integrate the features for diagnosis [4]. In

these networks, the connection weights which represent the decision regions for various faults are usually formed through supervised training. Therefore, these networks require a sample set of measurement-fault data for training. Since such data is usually not available and is very expensive to generate, the applicability of supervised networks is limited in practice.

In this paper, a diagnostic method is proposed that, while utilizing the measurement integration capability of connectionist networks, incorporates the proximity effect of components on sensors so as to eliminate the need for supervised training. Ideally, in order to accurately account for the proximity effect of components on the vibration features, the strength of the vibration signal from the components at the frequencies represented by the features needs to be modeled. This requires modeling the attenuation of vibration at these frequencies as the vibration travels from the components to the sensors. However, such a modeling task is difficult to perform, because: (1) the correct values of the stiffness and damping coefficients in the path cannot be accurately determined due to their time-varying and non-linear nature [5,11], and (2) it is not possible to evaluate the attenuation of vibration for the multitude of paths between components and sensors [10,6].

As a compromise to accurate attenuation levels for individual vibration features, in the proposed method the average attenuation of vibration across all frequencies is used to represent the overall proximity effect of gearbox components. In order to obtain the average attenuation, the gearbox is represented by a simplified lumped mass model, and the Root Mean Square (RMS) value of the vibration from this model is used to characterize the average attenuation. These RMS values are then used to assign *structural influences* representing the proximity effect of the components on the sensors. In order to account for the approximate nature of the simplified gearbox model, in the proposed method the *structural influences* are represented by fuzzy variables.

The *structural influences* only constitute the knowledge of the gearbox structure. So, there is a need to represent the relation between component faults and vibration features separately. Since vibration features are usually obtained at specific frequencies that are associated with the rotational frequency of individual components [8], their relation to various components is readily available. This relation is used to assign the *featural influences* representing the effect of component faults on features. The *structural influences* and *featural influences* are incorporated as weights of a *Structure-Based Connectionist Network* (SBCN) for diagnosis, which propagates abnormal

features through its fuzzy influence weights to calculate fault possibility values for each component in the gearbox.

2. STRUCTURE-BASED CONNECTIONIST NETWORK

The schematic of the *Structure-Based Connectionist Network* (SBCN) is shown in Figure 1. The inputs to this system are the abnormal vibration features obtained from processing the vibration measurements and flagging them based on the degree of abnormality. These *flagged* features are then used for both detection and isolation of faulty components. The task of flagging in the proposed system is performed by the unsupervised *Single Category-Based Classifier* (SCBC)[7] which classifies the features by comparing them with their values recorded during normal operation of the gearbox. Diagnosis is performed by propagating the n flagged values of the vibration features $f_i(t)$ through the SBCN, and obtaining as outputs the fault possibility values associated with individual gearbox components as:

$$p_k(t) = \sum_{i=1}^{n} f_i(t) w_{ik} \qquad (1)$$

where the w_{ik} represent the weighting factors determined based on the lower and upper bounds of the fuzzy influences (l_{ik} and u_{ik}) between the ith sensor and kth component as:

$$w_{ik} = l_{ik} + (u_{ik} - l_{ik}) f_i(t). \qquad (2)$$

In SBCN, in order to make uniform interpretation of the fault possibility values $p_k(t)$, they are normalized to have values between 0 an 1 as:

$$c_k(t) = \frac{p_k}{\sum_{i=1}^{n} u_{ik}} \qquad (3)$$

3. EXPERIMENTAL

The effectiveness of the SBCN was demonstrated using vibration data from an OH-58A helicopter main rotor gearbox (see Fig. 2). Vibration data was collected at the NASA Lewis Research Center as part of a joint NASA/Navy/Army Advanced Lubricants Program. Various component failures in an OH-58A main rotor transmission were produced during accelerated fatigue tests [3]. The vibration signals were recorded from eight piezoelectric accelerometers (frequency range of up to 10 KHz) using an FM tape
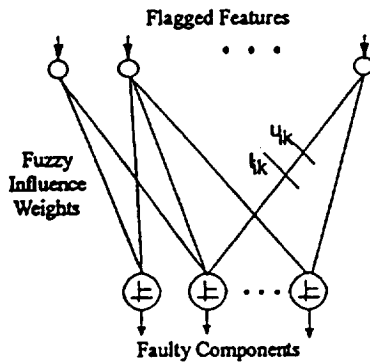
Figure 1: Schematic of the *Structure-Based Connectionist Network* (SBCN).

recorder. The signals were recorded once every hour, for about one to two minutes per recording (using a bandwidth of 20 KHz). Two magnetic chip detectors were also used to detect the debris caused by component failures.
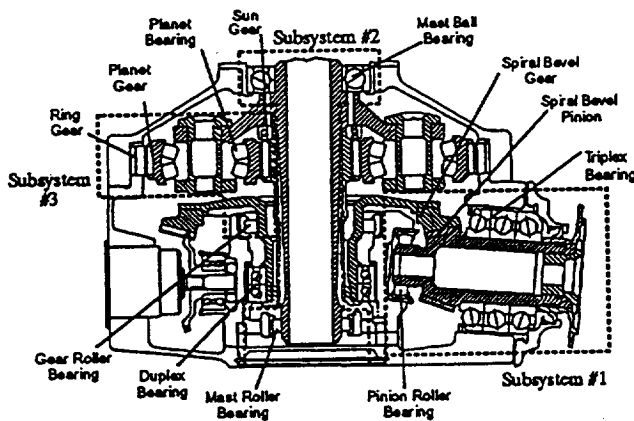

Figure 2: Layout of the various components in the OH-58A gearbox. The figure also shows division of the gearbox into subsystems for diagnosis.

In these experiments the gearbox was run under a constant load and was disassembled and inspected periodically, or when one of the chip detectors indicated a failure. A total of five tests were performed, where each test was run between nine and fifteen days for approximately four to eight hours a day. Among the eleven failures which occurred during these tests, there were three cases of planet bearing pitting fatigue, three cases of sun gear pitting fatigue, two cases of top housing cover cracking, and one case each of spiral bevel pinion pitting fatigue, mast bearing micropitting, and planet gear pitting fatigue. Insofar as fault detection during these tests, the chip detectors

were reliable in detecting failures in which a significant amount of debris was generated, such as the planet bearing failures and one sun gear failure. The remaining failures were detected during routine disassembly and inspection.

In order to identify the effect of faults on the vibration data, the vibration signals obtained from the five tests were digitized and processed by a commercially available diagnostic analyzer [8]. For analysis purposes, only one data record per day was used for each test. Overall, fifty four vibration features were extracted for each accelerometer. Out of these, nineteen features were indicators of general faults, whereas the other thirty five features were synchronous time averaged signals which related to specific gears in the gearbox. The detailed description of these parameters is included in [2].

4. RESULTS

For fault diagnosis of the OH-58A gearbox, the influences between the gearbox components and the eight accelerometers were obtained. For this purpose, five primary *vibration travel paths* in the gearbox were modeled using lumped mass modeling. These paths consisted of: (1) Duplex Bearing to Triplex Bearing through Spiral Bevel mesh, (2) Duplex Bearing to Ring Gear through the Sun-Planet mesh, (3) Mast Roller Bearing to Mast Ball Bearing through the Main Shaft, (4) Ring Gear to Mast Ball Bearing through Planet Bearing, and (5) Duplex Bearing to Mast Ball Bearing through the Sun-Planet mesh. Based on the lumped mass model of these paths, the RMS values were calculated for excitation sources at each gearbox component. The fuzzy influences between each of the components and the accelerometers were then obtained using these RMS values.

Diagnosis of the OH-58A gearbox was performed in three different hierarchies. In the top hierarchy, faults in the three subsystems of the gearbox (see Fig. 2) were isolated. The fuzzy influences between the three subsystems and the eight accelerometers were obtained by averaging the influences of the components in each subsystem, as shown in Table 1, and were incorporated as the weights of the top SBCN subsection. The inputs to this sub-section of SBCN were the averaged values of all abnormal features from each accelorometer, and its outputs were the fault possibility values for the three subsystems. In the second hierarchy, faulty component families (gear and bearing) in each subsystem were isolated. The inputs to the SBCN in this hierarchy were eleven of the nineteen features which were general indicators of faults, and its outputs were the fault possibility values for gear

and bearing family faults associated with the three subsystems. For this level of diagnosis, the featural influences (see Table 2) were scaled by the subsystem influences and were used as the weights of the second SBCN sub-section.

In the third hierarchy of SBCN, faults in individual components were isolated by using the synchronous time averaged features as inputs. Since for the OH-58A gearbox only the features associated with gears were available, the third sub-section of the SBCN was designed to only isolate faults in gears. The weights of this sub-section consisted of featural influences associated with the synchronous time averaged features which were scaled by the subsystem influences.

Accelerometer #	Subsystem #		
	1	2	3
1 (Top Cover)	-	L	H
2 (Top Cover)	-	H	M
3 (Top Cover)	-	H	M
4 (Input Bevel Housing)	H	-	L
5 (Input Bevel Housing)	H	-	M
6 (Ring Gear Housing)	M	L	H
7 (Top Cover)	-	L	H
8 (Ring Gear Housing)	-	L	H

Table 1: Influences of the three subsystem on the eight accelerometers. The influences shown are: '-' Nil, L Low, M Medium, and H High.

Based on the three sub-sections of SBCN, fault possibility values for subsystems, component families, and gears were obtained. In SBCN, fault isolation is performed only when a fault is detected by the flagging/detection stage. For brevity, only diagnostic results from the second SBCN are presented in this paper (see Table 3). In order to present the results in simplified format, the fault possibility values obtained from SBCN were hard-limited with a threshold of 0.5. As such, the results in Table 3 only list the component families with fault possibility values greater than 0.5. For comparison, the actual condition of the gearbox reported from routine inspection is listed inside brackets. It should be noted that faults may have occurred earlier than they were detected. For example, the faults in test #1 were only found upon routine disassembly of the gearbox on day 9. These faults had most probably occurred several days earlier, but remained unnoticed.

The results in Table 3 indicate that the SBCN identified the two gear family faults in subsystems 1 and 3

Feature	Subsystem #					
	1		2		3	
	G	B	G	B	G	B
1 (R)	M	M	-	M	M	M
2 (R)	M	M	-	M	M	M
3 (R)	M	M	-	M	M	M
4 (R)	M	M	-	M	M	M
5 (G)	D	-	-	-	L	-
6 (B)	-	L	-	L	-	D
7 (G)	D	-	-	-	L	-
8 (B)	-	L	-	L	-	D
9 (B)	-	H	-	H	-	H
10 (B)	-	H	-	H	-	H
11 (B)	-	H	-	H	-	H

Table 2: Featural influences of the gear G and bearing B families. The influences shown are: '-' Nil, L Low, M Medium, H High, and D Definite influences. The characters shown in parenthesis indicate that the associated feature reflects (G) Gear faults, (B) Bearing faults, and (R) both gears and bearings faults.

for test #1 on days 5, 7, and 8. However, the SBCN indicated a no-fault condition on day 6, where the fault should have been present. This is perhaps due to increased levels of noise in the vibration signal generated immediately after the occurrence of faults in the gearbox, which mask the effect of fault on the vibration signal. The SBCN also misdiagnosed faults in bearings of subsystem 1 and 3 on days 5 and 7 of test #1. This misdiagnosis is due to the presence of abnormality in vibration features which are common to both gear and bearing families. In test #2, the SBCN correctly identified all nine days as normal. In test #3, the bearing fault in subsystem 3 was correctly identified. However, because of common gear and bearing features, the SBCN again misdiagnosed a gear fault on days 3 and 4. There is also a carry over misdiagnosis from the first sub-section of SBCN on days 3 and 4, when faults in subsystem 1 were incorrectly diagnosed. In test #3, two bearing faults in subsystems 2 and 3 were correctly identified on day 12, however, they were misdiagnosed as gear faults on days 11 and 12. In test #4, the bearing fault in subsystem 3 was correctly identified on day 10, however, on the next day this fault was misdiagnosed as gear fault. Also in this test a carry over misdiagnosis from the first sub-section of SBCN in subsystem 2 appears as a misdiagnosed bearing fault on day 12. On day 13 of test #4, even though the gearbox was supposed

to be normal, the SBCN indicated faults in subsystems 2 and 3. This is due to a new fourth planet gear being installed on this day which caused abnormal values in the vibration features associated with subsystems 2 and 3. The SBCN also correctly identified the gear family fault in subsystem 3 on days 14 and 15 of this test. In test #5, the first 8 days were correctly identified as normal and a gear fault in subsystem 3 was diagnosed. There was also one misdiagnosis in subsystem 1 on day 9 of this test. In summary, this sub-section of SBCN was able to correctly identify normal gearbox operation on 30 of 31 days and diagnose all the 8 faults in the gearbox. However, it also produced 9 misdiagnoses.

Day	#1	#2	#3	#4	#5
1	- (-)	- (-)	- (-)	- (-)	(-)
2	- (-)	- (-)	- (-)	- (-)	(-)
3	- (-)	- (-)	G_1, B_1(-) G_3, B_3(-)	- (-)	(-)
4	- (-)	- (-)	G_1, B_1(-) G_3, B_3(B_3)	- (-)	(-)
5	G_1, B_1(-) G_3, B_3(-)	- (-)	- (-)	- (-)	(-)
6	- (-)	- (-)	- (-)	- (-)	(-)
7	G_1, B_1(-) G_3, B_3(-)	- (-)	- (-)	- (-)	(-)
8	G_1 (-) G_3 (-)	- (-)	- (-)	- (-)	(-)
9	- (G_1) - (G_3)	- (-)	- (-)	- (-)	G_1,G_3 (-)
10 11 12			- (-) G_1 (-) B_2 (-)	B_3 (-) G_3, (-) G_3, B_2 (B_3)	(-) (G_3)
13			G_1,B_3 (-) (B_2) (B_3)	G_3, B_2 (-)	
14 15				G_3(-) G_3(G_3)	

Table 3: Diagnosed faulty component families for the five tests. A 'G' represents the gear family fault, 'B' the bearing family fault, and '-' denotes no fault. The subscripts indicate the three subsystems. For reference, the observed faults are included inside parentheses.

5. CONCLUSION

A diagnostic method for helicopter gearboxes is introduced that uses knowledge of gearbox structure and characteristics of the vibration features to define the influences between the features and faults. This method brings together the diverse areas of dynamic modeling, fuzzy systems, and neural networks for the purpose of modeling the gearbox structure, representing the diagnostic knowledge and performing diagnosis, respectively. The proposed diagnostic method was evaluated using experimental vibration data from an OH-58A helicopter gearbox and showed promising results. The problems that were detected in these results relate to the fault detection phase of the method as well as its hierarchical diagnosis procedure. Further work needs to be done in order to finalize these aspects of the method.

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